

Modeling Statistics of Fish Patchiness and Predicting Associated Influence on Statistics of Acoustic Echoes

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LONG-TERM GOALS

To accurately describe the statistics of acoustic echoes due to the presence of fish, especially in the case of a long-range active sonar. Toward this goal, fundamental advances in the understanding of fish behavior, especially in aggregations, will be made under conditions relevant to the echo statistics problem.

OBJECTIVES

To develop new models of behavior of fish aggregations, including the fission/fusion process, and to describe the echo statistics associated with the random fish behavior using existing formulations of echo statistics.

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APPROACH

The research begins with development of new advanced models of fish behavior inspired by, and grounded by, existing 3-D images of fish aggregations. These images are derived by multi-beam acoustic systems. Key parameters to be observed and modeled are the fission/fusion rate of the aggregations. Concurrent with the modeling of fish behavior, statistics of fish aggregations, as they become available, will be incorporated into an existing general formulation for echo statistics. The results of this echo statistics model will, in turn, help to drive further development of the fish behavior model. In parallel to these efforts, other groups in the BRC will be conducting measurements. The Stanton/Weber/Grunbaum group will participate in planning those experiments which may have a component that reveals key aspects of fish behavior and, in turn, contribute to the modeling.

Stanton oversees the entire program as well as works with Weber on incorporating fish behavior models into echo statistics predictions. Weber also provides images of fish aggregations that he and others have collected. Grunbaum develops the fish behavior models.

WORK COMPLETED

Much time was spent at the beginning of the year conceptualizing the problem, as new ground will be broken on modeling of fish behavior based on insight and data derived from multibeam acoustic data. A set of tasks were formulated and then executed. They include 1) Weber producing images of fish schools that he or others have collected in the ocean through use of multibeam sonar and 2) Grunbaum developing a novel approach toward modeling the fission/fusion process of fish behavior. Details are given below:

1. High resolution images of fish aggregations derived from acoustic multibeam data

From several different candidate data sets (e.g., herring schools observed with 30 kHz mid-frequency omnidirectional sonar; aerial imagery and high-frequency multibeam data of Atlantic bluefin tuna), data from the NOAA Alaska Fisheries Science Center acoustic/rawl walleye pollock surveys (courtesy of Chris Wilson) were selected for this project. These data were collected with Simrad ME70 Multibeam Echosounder (MBES) on the NOAA Ship *Oscar Dyson* in 2010 in the Eastern Bering Sea and in 2011 in the western Gulf of Alaska. The ME70 MBES was designed specifically for fisheries research with several advantages over other types of MBES including very low sidelobes (< -60 dB), low self noise, high dynamic range, and the ability to be calibrated using standard target sphere methods that are commonly used for calibrating split-beam echo sounders. The NOAA survey data have a very large sample size (data are collected over 1000's of km of trackline, embodied in several terabytes of raw data which has been transferred to UNH data servers) and are periodically 'ground-truthed' with trawls for composition and size distribution. One of the disadvantages of this data set is that there are few repeat observations of the same aggregation (except, possibly, during trawls), which makes it difficult to extract the time-series information for direct comparison to the model efforts. On the other hand, these data offer a possible end-state comparison to the model runs.

MBES software analysis routines have been repurposed/developed in order to extract the fish aggregation data from the raw data (Figure 1a). Data processing begin on a ping-by-ping basis where potential seabed returns and sidelobe contamination are removed, and then a simple threshold ($S_v = -60$ dB) is used to identify fish target candidates (Figure 1b). The data from multiple pings are then

joined, filtered to remove ‘speckle noise’ (i.e., spatially isolated targets are considered noise and removed from subsequent analysis) and clustered. The clustering process provides a unique aggregation ‘ID’ to targets that are within 25 meters of each other horizontally and 5 meters of each other vertically. The clustering process is used mainly to remove undersampled data: aggregations that are observed on only two or fewer beams and on two or fewer pings are removed from any subsequent analysis. An example result of this data is shown in Figure 2, which includes a large ‘layer’ of adult Pollock, smaller aggregations of juveniles further up in the water column, and some areas where it becomes difficult to distinguish between the two.

The fish aggregation data extracted from the MBES data are geo-referenced ‘voxels’ (or points with a 3D extent) parameterized by a volumetric scattering strength (S_v). The scattering strength includes contributions from fish number density, as well as the angle dependent target strength of the fish which can depend on both the sonar beam angle, the possibly behavior dependent fish orientation, the size of the fish, etc. In order to be most directly comparable to the model outputs, it would be preferential to remove the angle dependent target strength from the data. To first order, the angle dependence can be normalized by assuming that there is no preferred fish orientation and that the angle-dependent target strength is stationary along the transect. This type of normalization is shown in Figure 3 for two example data sets. Here, the normalization is conducted separately at two different depths: greater than 100 m, corresponding to the layer of adult pollock, and less than 50 m, corresponding to the smaller aggregations of juvenile pollock. The resulting normalized data is expected to be proportional to the fish number density, with the caveat that biases due to species/size composition and/or behavior may be present in the result. However, this data can be directly compared to model results containing fish number density as an output.

2. Modeling fish school behavior

A novel approach has been developed towards understanding fission, fusion and migration of social groups by assuming a high level of sensory and cognitive function by interacting individuals. Simulations based on this model show all of these behavioral aspects, as illustrated in the time series of fish distribution in Figure 4.

Nearly all current models of social interaction are “zone models” which assume that characteristics of animal groups such as schools, swarms and flocks arise from individuals’ immediate responses to the relative positions and velocities of a small number of nearest neighbors. While there is little question that position- and velocity-dependent responses are crucial to social grouping, current zone models commonly predict that large groups (that is, groups in which individuals in different parts of a group must interact indirectly through many individuals between them) should be fragile and therefore rare or transient. However, natural groups are frequently large and stable. In other settings, natural populations that are sparse or distributed in numerous small groups nonetheless maintain common orientation across groups. In most current zone models, directionality can be maintained only by frequent encounters between individuals and groups, and so is unlikely in sparse populations at reasonable levels of behavioral and physical random forcing.

The model being developed assumes an additional cognitive layer in fish schooling behavior, in which encounters with neighbors are used as input data on which to base statistical estimates of the density and movement characteristics of the local population. The key idea is that each individual is continuously updating its understanding of the intent of its neighbors, and basing its own decision-

making on this understanding. Thus, social individuals can glean information even when the instantaneous position and velocity of neighbors are quite different from overall movement patterns, or when neighbors are so sparse that encounters with them are rare.

The above line of reasoning suggests a new hybrid model that combines agent-based “Lagrangian” movement rules with a “Eulerian” distribution of population density and flux, together with local distributions of orientation angle. This hybrid approach has multiple advantages from the perspective of understanding acoustic signatures of fish in real-world settings. One is computational tractability: Agent-based models of social grouping are inherently N^2 computations, where N is the number of individuals. (Specifying maximum interaction distances can enable subdivision of the habitat into non-interacting parts, but computational requirements remain large for dense groups.) The hybrid model executes parallel simulations, in which the estimates of local population characteristics evolve as partial differential equations, and the individuals respond to estimates as autonomous agents. Hence, there is no N^2 calculation required. Another advantage of our hybrid approach is that the statistical distributions calculated during social simulations (population density, orientation angles, etc.) are directly relevant to estimate of acoustic signatures.

The hybrid modeling being developed assumes a Bayesian framework for local estimation of population movement. For example, for estimates of local density, we assume each individual maintains a Bayesian updating scheme for determining the expected value and uncertainty associated with the Poisson distribution of neighbors. In a standard updating scheme, appropriate for statistically stationary neighbor distributions, the uncertainty decreases monotonically with ongoing sampling. In application to schooling, in which populations move and therefore are not statistically stationary, we discount the predictive value of old information. Hence, an individual's uncertainty about local density and direction fluctuates downwards when informative samples occur frequently and upwards when such samples are rare.

RESULTS

Development of a novel method toward modeling fish behavior is in process and has yielded promising (although preliminary) results. Fission, fusion, and migratory behavior of the fish are being modeled. These results use a hybrid approach that integrates both intelligence of the fish in nearest neighbor interactions as well as group behavior. These results were motivated, in part, through many acoustically-derived images of fish aggregations and may lead to a new capability of realistic modeling of fish behavior.

IMPACT/APPLICATIONS

This new model of fish behavior, still under development, will represent an advancement of the fundamental understanding of fish behavior, given the new capability (fish intelligence) and the grounding with observed images of fish aggregations in the ocean. Also, through accurate modeling of distributions of fish and their temporal evolution, this will improve our ability to predict acoustic scattering and associated echo statistics, which is relevant to Navy ASW applications.

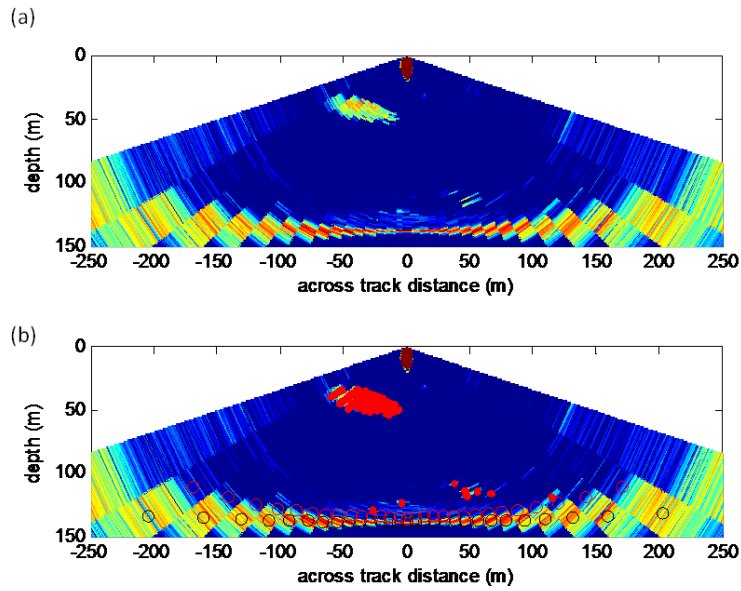


Figure 1. (a) A single raw ping of ME70 MBES data, with a small aggregation of fish located at (-40 m, 40 m). (b) Automatically detected potential fish targets (red dots) after removal of data below the seabed returns (red circles).

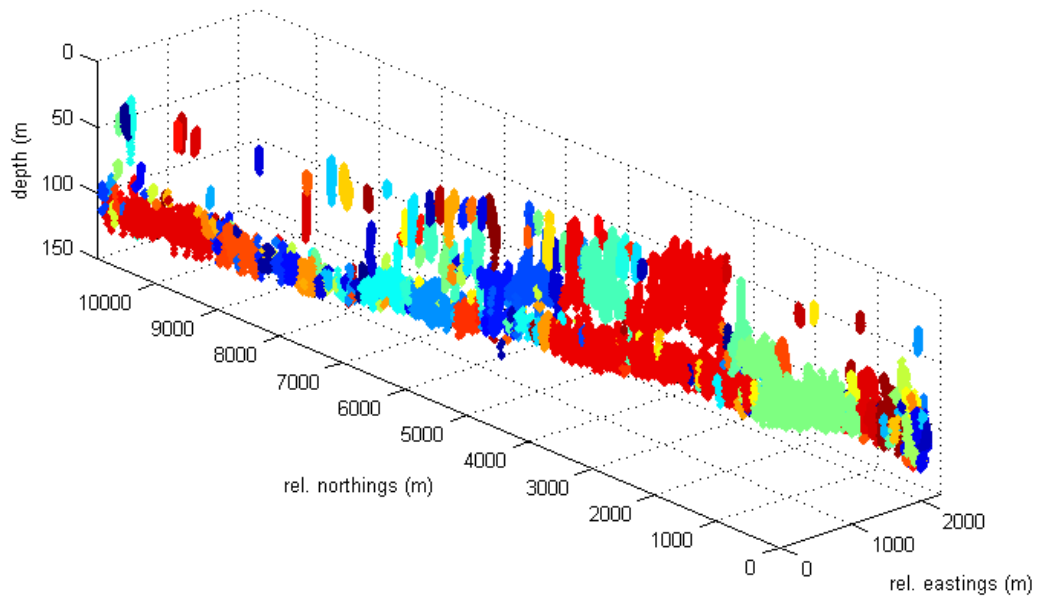


Figure 2. ME70 MBES targets classified as fish including both adult pollock (large lower layer) and smaller aggregations of juvenile pollock.

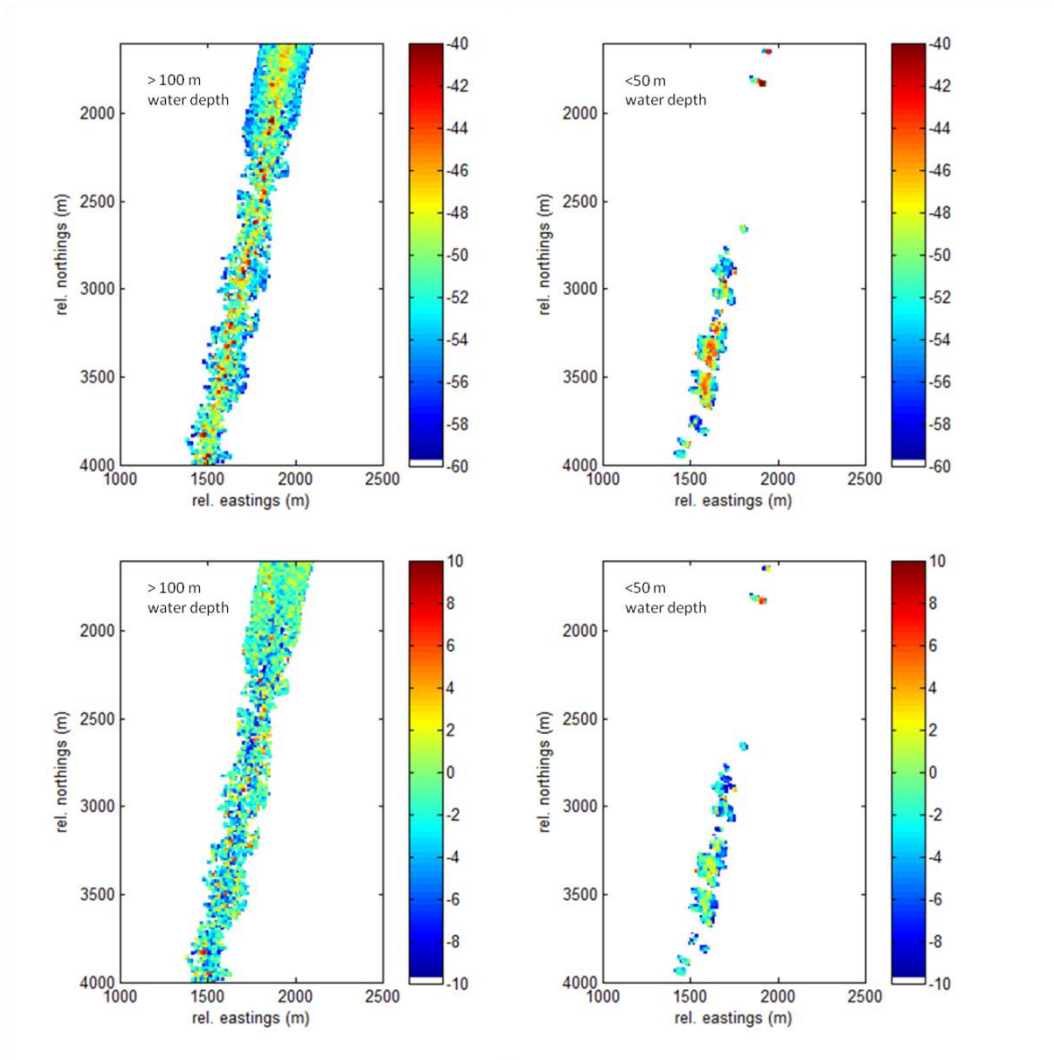


Figure 3. *Upper figures: Average volume scattering strength (S_v) for the lower layer (> 100 m water depth) of adult pollock and the smaller aggregations of juvenile pollock in water depths < 50 m. Lower figures: Average S_v after normalization, a proxy for fish number density.*

Fusion-fission dynamics model

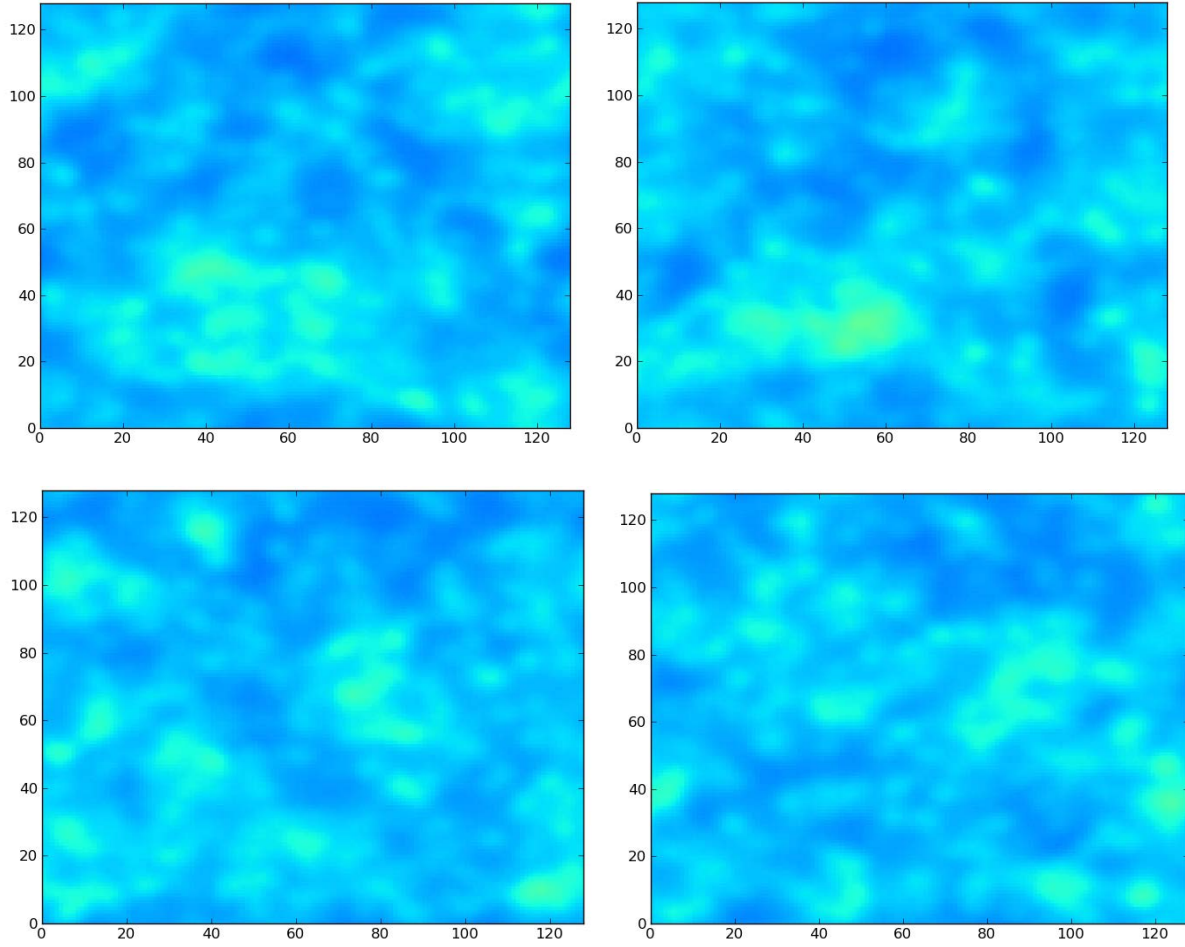


Figure 4: Fusion-fission dynamics in the Bayesian fish schooling model represented by the new density distribution derived. The figures show a sequence of coalescence to form a large compact group, followed by its fragmentation and dispersal. This sequence is typical of an on-going process of dispersal and reaggregation in the schooling simulation.